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BIOMORPHIC NETWORKS FOR ATR AND HIGHER-LEVEL PROCESSING

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During the period of this report we derived an expression for the upper bound on the number N_s of possible states a dynamical network of N processing elements (PEs) whose elements can take on period-m orbits where $0 \leq m \leq L$, L being the number of distinguishable levels over which the state $X_i(n)$ of the i-th PE in the network is measured. Note $m = 0$ designates $X_i(n) = 0$ i.e. an inactive element and $m = 1$ designates an element with fixed point orbit $X_i(n) = \text{const}$. For large L we find

$$N_s = [eL!]^N \tag{1}$$

In comparison, the number of possible state of a neural network of the same size but employing sigmoidal analog neurons whose states are resolved over L distinguishable levels is $N_s = L^N$. A dynamical network that can exhibit periodic activity has therefore the advantage of a much higher number of states than a conventional network, with no periodic activity; in fact $[e(L-1)!]^N$ times more states. The advantage of dynamical networks becomes even more striking when one considers that in our Parametrically coupled logistic map net (PCLMN) studied earlier [1] with $N = 100$ and assuming say $L = 256$ (8 bit resolution) the number of possible states $[e\,256!]^{100}$ is astronomical. All of these states are in principle accessible by extrinsic stimuli giving it enormous classification power as compared for example to a neural net with analog neurons such as Anderson's "Brain State in a Box" (BSB) network [2] which has a maximum of 2^N possible states which occurs only when its connection matrix is strongly diagonal-dominant [3]. What is interesting is that both the BSB net and the PCLMN utilize random coupling matrixes that are strongly diagonal-dominant. Also both can classify a large number of input stimuli, one the PCLMN with the help of $(eL!)^N$ coexisting attractors that can be accessed by the stimuli and the second the BSB with help of 2^N coexisting attractors that are accessible by the stimuli. The major difference is that the PCLMN can handle dynamic input patterns while the BSB only static input patterns applied as the initial state of the network. Because most natural and artificial stimuli are dynamic in the form of spatio-temporal patterns, the utility of the BSB as a classifier net is limited. This limitation does not apply to the PCLMN which can classify or categorize an immense number of environmental stimuli that can be either dynamic or static. Because the output of the PCLMN is also dynamic (a compact dynamic attractor CDA see [1] for detail), it can be regarded as a short-term memory (STM)

trace characterizing the applied stimulus. Such STM traces will be used in our future research to drive a second PCLMN with an autonomous adaptable coupling factors matrix that can learn to convert STMs into permanent long-term memories (LTMs). Our goal is to come up with a learning algorithm that enables learning STMs without cross-talk, (interference) between the formed memories (LTMs) and to achieve large storage capacity. Achieving this goal would provide us with a corticonic network consisting of a tandem connection of two PCLMNs one with fixed coupling for the creation of STMs and the second, with adaptable coupling and most probably global coupling, for the conversion of STMs into LTMs with no cross-talk and high storage capacity.

The development of such a hierarchical corticonic network will be an important step for the design of machines with brain-like intelligence. These will be machines that can autonomously learn from a complex uncontrolled environment and have inbuilt ability to recognize novel inputs in order to learn them automatically while recognizing a familiar input immediately by recreating its appropriate learned response without activating the learning. This is basically the "Holy-Grail" in neural networks and brain modeling. Realizing it would have far reaching implications and will open new possibilities for the design of intelligent systems of interest to ONR. This will be a critical milestone in our research program which we are reasonably confident we can achieve. It is expected to call for an expansion of the program in order to deal with the many new research opportunities that would be opened then.

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